Seasonal Modulation of the Madden–Julian Oscillation’s Impact on Rainfall in Sri Lanka

CHANUD N. YASANAYAKE, a BENJAMIN F. ZAITCHIK, a AND ANAND GNANADESIKAN

a Department of Earth and Planetary Sciences, The Johns Hopkins University, Baltimore, Maryland

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ABSTRACT: For the tropical country of Sri Lanka, subseasonal variability in precipitation is both ecologically and socially relevant, influencing agricultural yields, natural hazard risk, energy production, and disease incidence. The primary driver of this subseasonal precipitation variability is the Madden–Julian oscillation (MJO). Here we investigate this influence on Sri Lankan precipitation across seasons, describing MJO-associated precipitation patterns and exploring the potential for MJO-informed subseasonal forecasts. We do so using 40-yr satellite-derived records of precipitation with high spatial resolution (from CHIRPS v2.0) and related meteorological and atmospheric fields (from ERA5 and MERRA-2). We find a direct MJO influence on precipitation corresponding to propagation of the MJO’s convectively active region and suppressed region near Sri Lanka, with the strength and spatial patterns of this influence differing across seasons. There are particularly strong impacts in the second intermonsoon (SIM; October–November) and southwest monsoon (SWM; May–September) seasons. During SIM the impacts are island-wide, but strongest in the northeast. During the SWM the absolute impacts are localized to the southwest, but the relative impacts (i.e., relative to precipitation climatology) are fairly uniform across the island. Moreover, we find significant associations between MJO phase and Sri Lankan precipitation at time scales of up to several weeks. Notably, these associations are stronger when using the OLR-based MJO index (OMI) rather than the more commonly used real-time multivariate MJO index (RMM). While the MJO associations we describe here arise from a highly simplified forecasting scheme, they provide a foundation and impetus for developing a more complete, MJO-informed precipitation forecast method.

SIGNIFICANCE STATEMENT: Rainfall variability at the subseasonal (weeks–months) time scale is critical to societal well-being, given its fundamental importance for agriculture, flood risk, hydropower generation, and disease incidence. Our work describes how such rainfall variability in Sri Lanka is impacted by the Madden–Julian oscillation, in which a region of enhanced rainfall and cloudiness, paired with a region of decreased rainfall and cloudiness, circles the globe every 30–60 days. Our results suggest that its influence on Sri Lankan rainfall may be strong enough that incorporating knowledge of the Madden–Julian oscillation into forecasts can improve the accuracy of rainfall prediction for Sri Lanka. Future work should develop a more comprehensive forecast method to assess viability in real-world forecasting scenarios.

KEYWORDS: Tropics; Madden-Julian oscillation; Precipitation; Satellite observations; Forecasting; Subseasonal variability

1. Introduction

Nested in the central Indian Ocean, the island country of Sri Lanka lies near the equatorial path of the Madden–Julian oscillation (MJO): the dominant driver of tropical climate variability at the subseasonal time scale (Madden and Julian 1994). At this time scale (weeks to months), the variability of Sri Lankan climate—and particularly of rainfall—can have far-reaching ecological and societal impacts, including on agriculture, hydropower generation, flood and landslide risk, and mosquito-borne disease incidence (Jayawardena et al. 2020, 2022; Mahanama et al. 2008; Vuillaume et al. 2018). This presents a strong incentive for understanding the subseasonal patterns of Sri Lankan rainfall and the role of the MJO therein.

The impact of the MJO is critical to this subseasonal rainfall variability. However, most past research on this subject has either been highly focused in temporal scope, discussing MJO impacts during a single season or specific extreme rainfall event (Mishra et al. 2017; Viallard et al. 2011; Jayawardena et al. 2017), or has had a broad spatial scope, discussing MJO impacts over the entire Indian subcontinent (Anandh et al. 2018; Anandh and Vissa 2020). To our knowledge only one study, Jayawardena et al. (2020), has assessed MJO precipitation impacts in all four of Sri Lanka’s seasons and for each of the MJO’s eight life cycle phases, finding a direct association between MJO-associated precipitation anomalies and the proximity of the MJO’s convectively active and suppressed regions. Their work provides an essential understanding of the
MJO’s impact on Sri Lankan rainfall, yet also offers new questions that we explore in this work: how robust are these results to varied methods of MJO analysis, what are the mechanisms of MJO impact, and to what extent does MJO state inform forecasting of precipitation? In section 3a we consider the first question of robustness, expanding on the work of Jayawardena et al.—which used 44 individual rain gauges and CHIRPS v2.0 satellite data from 1981 to 2010—by incorporating 10 additional years of meteorological data, additional data processing and filtering to isolate MJO-associated meteorological signals, and an alternative index for representing the MJO amplitude and phase [OMI rather than RMM, as discussed in section 2a(2)]. Then we consider mechanisms of MJO impact by examining the corresponding large-scale anomalies in a suite of MJO-relevant meteorological variables (section 3b) and the associated changes in diurnal rainfall cycle for climatically distinct regions of Sri Lanka (section 3c). Finally, we use these results for a preliminary assessment of forecasting potential (section 3d): can MJO information be used to skillfully forecast anomalous rainfall? In doing so we develop a more robust understanding of Sri Lankan subseasonal rainfall and the climatic influence of the MJO.

a. Sri Lanka’s seasonal climate

Sri Lanka’s climate is primarily driven by the South Asian monsoon, whose shifting large-scale patterns of winds and precipitation define the island’s four seasons: the northeast monsoon (NEM; December–February), first intermonsoon (FIM; March–April), southwest monsoon (SWM; May–September), and second intermonsoon (SIM; October–November) (e.g., Sumathipala 1980; Nisansala et al. 2020). The seasonal migration of the intertropical convergence zone (ITCZ) brings precipitation to the island as well, passing from south to north over Sri Lanka during the first intermonsoon season and passing from north to south during the second intermonsoon season (Suppiah 1989; Lashkari et al. 2017). Here we refer to rainfall and precipitation interchangeably, as rainfall is essentially the only form of precipitation in Sri Lanka aside from rare hail events (Thambyahpillay 1954).

Both rainfall and temperature have distinct spatial patterns across the island on account of topography (Fig. 1; note the correspondence between elevation gradient and annual mean temperature/precipitation). The central highlands are cooler than the low-lying plains and coastal regions and also divide the island into its primary climatic zones: the wet zone in the southwest (>2500 mm annual rainfall), the dry zone in the north and east (<1750 mm), and an intermediate zone in between (1750–2500 mm) (e.g., Jayawardena et al. 2020; Karunathilaka et al. 2017; Nisansala et al. 2020). Although temperature varies minimally across seasons, rainfall shows substantial seasonal variability, with the greatest mean daily rainfall in the second intermonsoon season (October–November). There is also a clear orographic effect, where rainfall is intensified on the side of the highlands facing the monsoon winds (e.g., the island’s east side in the NEM season, southwest side in the SWM season).

While these seasonal aspects of Sri Lanka’s climate are well known, what is less studied is climatic variability within each season: how does the climate vary on subseasonal time scales of a few weeks to months? To investigate subseasonal climate patterns we have focused specifically on the impact of the Madden–Julian oscillation.

b. The Madden–Julian oscillation

The quasiperiodic atmospheric phenomenon known as the Madden–Julian oscillation (MJO) has been widely studied since its discovery over 50 years ago (Madden and Julian 1971), not only for its dominant role in subseasonal climate variability in the tropics (Madden and Julian 1994) but also for its near-global meteorological effects via teleconnections (Donald et al. 2006). This wide-ranging climatic influence includes impacts on rainfall variability, tropical cyclone formation in the Pacific Ocean and Caribbean Sea, equatorial surface winds in the Atlantic Ocean, the cycles of El Niño–Southern Oscillation, and Earth’s electric and magnetic fields (Zhang 2005; DeMott et al. 2015). Here we briefly summarize the most salient aspects of MJO structure and characteristics, although readers interested in a more comprehensive understanding are encouraged to consult the extensive MJO literature (e.g., Zhang 2005; Lau and Waliser 2012; Adames and Wallace 2014a,b).

The MJO can be described as a large-scale atmospheric disturbance of coupled circulation and deep convection, originating in the equatorial Indian Ocean and propagating eastward at ~5 m s$^{-1}$ (Fig. 2). It has an east–west oriented pattern of two distinct features: a convectively active region (enhanced precipitation) and a convectively suppressed region (suppressed precipitation). These two features are linked by overturning zonal circulations; in the lower troposphere (~850 hPa) zonal winds converge toward the convectively active region, while in the upper troposphere (~200 hPa) the zonal winds diverge (Zhang 2005).

The life cycle of an MJO event is commonly categorized into eight phases, beginning with the convectively active region’s formation in the Indian Ocean (phase 1) and ending with its decay in the Pacific (phase 8) (Wheeler and Hendon 2004). The time scale of this life cycle is variable, partially due to seasonal and interannual fluctuations, but is typically 30–60 days (Zaitchik 2017).

Seasonal effects influence MJO strength, latitude, and frequency. The MJO is strongest in boreal winter and spring, when its location is offset slightly south of the equator (e.g., Zhang and Dong 2004). A secondary peak in the MJO’s strength occurs in boreal summer, when it is slightly north of the equator (Madden and Julian 2012). The character of the MJO changes in boreal summer, with greater meridional propagation to the north of the equator. During this season the phenomenon is generally referred to as the boreal summer intraseasonal oscillation (BSISO) rather than the MJO (e.g., Wang and Xie 1997; Kikuchi 2021). However, in this paper we use the term MJO for all seasons, to simplify discussion.

The MJO’s equatorial path lies near Sri Lanka, and prior work has highlighted connections between the MJO and Sri Lankan rainfall. Heavy rainfall and flooding events are
associated with the proximity of the MJO’s convectively active region (Jayawardena et al. 2017; Anandh and Vissa 2020), while decreased rainfall is associated with the proximity of the MJO’s suppressed region (Vialard et al. 2011). However, note that the spatial scales of the convectively active region and suppressed region are much larger than the island of Sri Lanka, and that Sri Lanka often lies at the edge of these regions (Fig. 2). Therefore, small changes in
latitude or width of the convective anomalies with season, as well as interactions with the topography of Sri Lanka, have the potential to significantly modulate the response of precipitation to the MJO. In this work we explore these nuances of the MJO–rainfall relationship by analyzing both magnitude and spatial distribution of this anomalous rainfall across 1) each season and 2) each of the MJO’s eight phases.

![Composite maps of precipitation anomalies associated with each of the MJO life cycle’s eight phases, for each of Sri Lanka’s seasons: northeast monsoon (i.e., boreal winter), first intermonsoon, southwest monsoon, and second intermonsoon. Note the eastward propagation of the enhanced (green) and suppressed (brown) rainfall patterns. MJO phases are defined using the OLR-based MJO index (OMI). Data are daily ERA5 precipitation over 1981–2020 (Hersbach et al. 2020). Data have been filtered (20–100 day Lanczos bandpass) and data for which OMI amplitude < 1 have been excluded.](image)

### Data and methods

#### a. Data

1) **Meteorological and Atmospheric Data**

All meteorological and atmospheric data were from gridded data products (CHIRPS, ERA5, MERRA-2; described in detail below) and span a 40-yr time period (1981–2020). Analysis
is primarily conducted using daily data, although hourly ERA5 data are used for analysis of Sri Lanka’s diurnal rainfall cycle.

For precipitation we primarily used the Climate Hazards Group Infrared Precipitation with Station (CHIRPS v2.0) data (Funk et al. 2015). CHIRPS combines historical climatology, satellite-based cold cloud duration precipitation estimates, and station-based rain gauge observations to produce quasi-global (50°S–50°N), high-resolution (0.05°) precipitation daily estimates. We use this satellite-derived product rather than station data due to 1) the sparseness of stations in the northern and eastern regions of Sri Lanka and 2) gaps in station data records during periods of conflict (Wijemannage et al. 2016; Jayawardena et al. 2020). Although CHIRPS is known to underestimate precipitation relative to ground-based station data in the central highlands of Sri Lanka (Jayawardena et al. 2020), it still correlates well with observations (Alahacoon and Edirisinghe 2021) and outperforms many other satellite-derived gridded data products for Sri Lankan precipitation (Bandara et al. 2022). The high resolution and broad spatial coverage of CHIRPS allow for a comprehensive analysis of precipitation variability across Sri Lanka.

CHIRPS’s limited spatial extent (only precipitation over land) and temporal resolution (daily) make it unsuitable for our analyses of large-scale circulation and of diurnal rainfall patterns. For these two analyses we use precipitation data from the ERA5 global reanalysis product (Hersbach et al. 2018b, 2020). ERA5 is produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) within the Copernicus Climate Change Service. It has a native spatial resolution of 0.25° × 0.25° (notably lower than CHIRPS) and an hourly temporal resolution. For the analysis of large-scale circulation these hourly data were averaged to daily values. Note that precipitation from reanalysis products (such as ERA5) is typically considered to have significant uncertainty and error in comparison to satellite-based precipitation data (Bosilovich et al. 2008; Gehne et al. 2016). Although there are such satellite-based products that, like ERA5, provide hourly precipitation over both ocean and land, we do not use them for this work because of their shorter temporal coverage [e.g., ~20 years for IMERG (Huffman et al. 2015)]. This would not only hinder direct comparisons with the ~40-yr CHIRPS record, but would also be a limited amount of data to draw meaningful conclusions from, particularly since our analyses are on subsets of the precipitation data (subdividing by the four seasons and eight MJO phases). So we opt to use ERA5 rather than satellite-based products, keeping in mind the caveats that come with using precipitation from reanalysis. In particular, ERA5 daily precipitation tends to have a wet bias and greater error in the tropics than the extratropics (Lavers et al. 2022), and our own analysis of ERA5 hourly precipitation shows differences in the diurnal cycle’s magnitude and an earlier time of peak precipitation in comparison with satellite-based IMERG hourly precipitation (Figs. S9 and S10 in the online supplemental material; discussed further in section 3c).

For the other meteorological variables used to assess the MJO’s large-scale atmospheric circulation we used both ERA5 (Hersbach et al. 2018a,b) and a second global reanalysis product, the Modern-Era Retrospective analysis for Research and Applications 2 (MERRA-2) (Global Modeling and Assimilation Office 2015a,b,c). MERRA-2 is produced by the NASA Global Modeling and Assimilation Office (GMAO) using the Goddard Earth Observing System Model (GEOS) version 5.12.4. It has a native spatial resolution of 0.5° × 0.625° and an hourly temporal resolution (averaged to daily values for this study). These two reanalysis products were used to gauge the robustness of our results. In other studies ERA5 tends to match observations better than MERRA-2 across variables such as precipitation (Hassler and Lauer 2021), top of atmosphere shortwave radiation (Lim et al. 2021), and cloud cover (Wu et al. 2023), although both have wet biases over tropical oceans (Hassler and Lauer 2021). In this work we found that the ERA5 and MERRA-2 meteorological fields were generally consistent with one another near Sri Lanka for our variables and scales of interest, with one notable exception: the ERA5 vertical pressure velocity fields revealed nuanced spatial heterogeneity over Sri Lanka that was lost to the coarser spatial resolution of MERRA-2. Given this, we show only the (higher resolution) ERA5 data here.

To study the large-scale circulation we examined patterns of outgoing longwave radiation (henceforth OLR), 500-hPa specific humidity, 500-hPa vertical pressure velocity (henceforth ω), and horizontal winds at 250 and 850 hPa. These pressure levels were chosen because they represent the lower (850 hPa), middle (500 hPa), and upper (250 hPa) troposphere values of these variables and are the pressure levels common to the specific ERA5 and MERRA-2 datasets used here. These meteorological variables were selected because they show characteristic signals during an MJO event. For example, the MJO’s convectively active region is characterized by anomalously low OLR due to enhanced cloud cover associated with deep convection. This is accompanied by anomalously low midtropospheric ω, which is a direct measure of convection, and anomalously high midtropospheric specific humidity, which facilitates deep convection (since such convection is inhibited less by entrainment of moist air than of dry air) (Natoli and Maloney 2019; Bretherton et al. 2004; Holloway and Neelin 2009, 2010; Yuan and Houze 2013; Gray 1979). Meanwhile the horizontal winds in the lower (upper) troposphere converge toward (diverge away from) the convectively active region (e.g., Zhang 2005; Rui and Wang 1990). Each of these meteorological patterns for the MJO’s convectively active region is inverted for the suppressed region (e.g., anomalously high OLR). Taken together, these variables help explain the patterns of MJO-associated precipitation over Sri Lanka in terms of large-scale MJO behavior.

2) MADDEN–JULIAN OSCILLATION INDEX

We characterized the Madden–Julian oscillation’s structure and evolution using daily amplitude and phase values for the same time period as the meteorological data (1981–2020). The amplitude (a nonnegative number) is a measure of MJO strength, with a value smaller than 1 considered a “weak” or
“inactive” MJO event (Wheeler and Hendon 2004; Laffleur et al. 2015). The phase (1 through 8) describes the geographic location of the MJO’s convectively active region as it propagates from the Indian Ocean to the Pacific. Amplitude and phase values used here are derived from the OLR-based MJO index (OMI) (Kiladis et al. 2014). OMI is based on an empirical orthogonal function (EOF) analysis of spatially gridded outgoing longwave radiation (OLR), where seasonal MJO variation is accounted for by using a 121-day sliding window to generate the daily EOFs. OMI is published as daily values of the first two principal component coefficients (PC1 and PC2), which we converted to amplitude and phase values as described by Kiladis et al. (2014).

This OMI-based definition of MJO amplitude and phase is analogous to amplitude and phase from the widely used real-time multivariate MJO (RMM) indices, a metric based on the first two EOFs of combined fields of OLR and upper/lower troposphere (850 and 200 hPa) zonal winds near the equator (Wheeler and Hendon 2004). However, while RMM indices are frequently used for MJO diagnostics, the OMI better captures the intraseasonal oscillation during boreal summer (Kiladis et al. 2014). We conducted our analysis using both RMM and OMI and generally found stronger or comparable MJO-associated rainfall signals in all seasons when using OMI, so we primarily present the OMI-based results here. However, there are important differences in the northeast monsoon and second intermonsoon seasons (see section 3), and we provide the RMM-based results in the supplemental material (Fig. S2).

In our analysis we typically exclude data from days for which OMI amplitude is less than 1 (i.e., weak MJO events). The only exception is when calculating climatologies, for which we use the full data record. The exclusion of data with OMI amplitude < 1 is necessary because of the manner in which OMI is mathematically constructed: spatial variability in tropical convection at any scale will generally have some nonzero projection onto the OLR-based modes used to construct the OMI, without necessarily being associated with the MJO phenomenon. Therefore, using the full data record would obfuscate the MJO signal with noise from non-MJO days. To reduce this noise and recover a clearer MJO signal, we choose an amplitude threshold at which a coherent MJO event is likely present. Here we use an amplitude threshold of 1 as it is widely used in the literature (for not only the OMI, but also for similarly constructed MJO indices such as RMM) (e.g., Kiladis et al. 2014; Wheeler and Hendon 2004).

### b. Data analysis

1) **SUBDIVIDING BY SEASON AND PHASE**

   In our analysis we subdivide the meteorological data according to (monsoon-based) season and (OMI-based) MJO phase. Notably, these seasons differ in length and the MJO phases do not occur with equal frequency in our data record. This is important because, given that we aim to understand the meteorological impact of the MJO on Sri Lanka, we are interested in not only the average strength of the MJO signal for each season–phase combination, but also how often each season–phase combination occurs.

   The seasons were defined as follows: northeast monsoon (NEM; December–February), first intermonsoon (FIM; March–April), southwest monsoon (SWM; May–September), and second intermonsoon (SIM; October–November). These definitions may vary from those found in other literature, as there is considerable variety in how Sri Lanka’s seasons are defined. Some studies define these same four seasons, but shift their timespans by up to a month (e.g., Wickramagamage 2016; Clark et al. 2012; Zubair et al. 2008). Other studies define only two seasons: the traditional agricultural seasons of *Yala* (approximately April–September) and *Mahua* (approximately October–March) (e.g., Zubair et al. 2008; Yahiya et al. 2009; Burt and Weerasinghe 2014; Nissanka et al. 2011). We chose to define four seasons (rather than two) for greater temporal precision, and we chose the timespans of these four seasons to match what we found most frequently in the literature (e.g., Mathanraj and Kaleel 2017; Nisansala et al. 2020).

   The MJO phases were defined based on OMI, as described in section 2a(2). Table 1 shows the frequency anomaly distribution of MJO phases in our 1981–2020 data record (excluding data for weak MJO events). Note that a uniform seasonal distribution of the eight MJO phases would correspond to

<table>
<thead>
<tr>
<th>MJO phase</th>
<th>NEM (DJF)</th>
<th>FIM (MA)</th>
<th>SWM (MJJAS)*</th>
<th>SIM (ON)*</th>
<th>Annual*</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.2%</td>
<td>-0.4%</td>
<td>-2.5%</td>
<td>-5.1%</td>
<td>-1.9%</td>
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<tr>
<td>2</td>
<td>0.0%</td>
<td>-0.6%</td>
<td>3.8%</td>
<td>1.6%</td>
<td>2.6%</td>
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<tr>
<td>3</td>
<td>-0.2%</td>
<td>0.6%</td>
<td>2.5%</td>
<td>3.0%</td>
<td>2.0%</td>
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<tr>
<td>4</td>
<td>0.5%</td>
<td>0.0%</td>
<td>-4.6%</td>
<td>-2.6%</td>
<td>-2.1%</td>
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<tr>
<td>5</td>
<td>-0.8%</td>
<td>-1.5%</td>
<td>-0.5%</td>
<td>-6.0%</td>
<td>1.6%</td>
</tr>
<tr>
<td>6</td>
<td>0.4%</td>
<td>0.9%</td>
<td>3.1%</td>
<td>1.9%</td>
<td>1.8%</td>
</tr>
<tr>
<td>7</td>
<td>-0.6%</td>
<td>0.2%</td>
<td>0.8%</td>
<td>4.3%</td>
<td>0.8%</td>
</tr>
<tr>
<td>8</td>
<td>0.9%</td>
<td>0.7%</td>
<td>-2.5%</td>
<td>-1.4%</td>
<td>-0.8%</td>
</tr>
</tbody>
</table>

*OMI-based MJO phases by season (as a percentage point difference relative to 12.5%, i.e., the uniform distribution frequency).

The phases were abbreviated as follows: NEM = northeast monsoon, FIM = first intermonsoon, SWM = southwest monsoon, SIM = second intermonsoon. The corresponding month ranges are indicated by initialisms (e.g., DJF = December, January, February). An asterisk indicates a statistically significant deviation from a uniform distribution (chi-squared test, 95% confidence level).
frequencies of 12.5%, which would be shown in Table 1 as frequency anomalies of 0.0%. Table 1 shows two distinct seasonal patterns: a fairly uniform distribution in the NEM and FIM seasons, and an uneven distribution in the SWM and SIM seasons (i.e., more days in phases 2, 3, 6, 7; fewer in phases 1, 4, 5, 8). These phases of increased frequency correspond geographically to when the MJO’s convectively active region is in the Indian Ocean (phases 2 and 3) or western Pacific (phases 6 and 7). The phases of decreased frequency correspond to either a convectively active region located over the Maritime Continent (phases 4 and 5) or to the transition-ary period between MJO events when there may be two convectively active regions: a decaying core in the central Pacific alongside a newly forming core near eastern Africa (phases 1 and 8).

These frequency distributions differ when the MJO phases are defined based on RMM (Table S2). While a thorough discussion of MJO frequency distribution falls outside the scope of this paper, further details on both OMI- and RMM-based MJO frequency distributions within our data are provided in supplemental material (Tables S1 and S2; Fig. S1). The salient points to keep in mind for this paper are that 1) the frequency of each MJO phase differs across seasons, and that 2) this frequency distribution is dependent on the index used to define MJO phase (OMI versus RMM).

2) FILTERING

All meteorological anomaly data were preprocessed to isolate temporal frequencies associated with the MJO. We did so using a 201-point 20–100-day bandpass Lanczos filter, as recommended by the MJO CLIVAR Working Group (Waliser et al. 2009). Note that this filtering results in data loss at both ends of the dataset (in this case with 201 weights we lose the first and last 100 days of data), so the filtered data do not quite span the entire 1981–2020 time period of the original dataset.

In this paper we primarily consider data that have undergone this filtering. In comparing composite maps of anomalies for both the filtered and unfiltered data (Fig. 3 and Fig. S3) we find that the overall spatial patterns of the anomalies are similar, but that in most cases the filtered composites show weaker anomaly signals than their unfiltered counterparts. The filtered composites also tend to yield spatially smoother anomaly plots.

An exception to using filtered data is in the section on forecasting potential, where we focus on unfiltered data. This is because the loss of data when filtering (specifically the loss of the most recent data in the record) makes the filtered data less appropriate for real-time forecasting applications.

3) COMPOSITE MAPS

For each meteorological variable we generated composite maps of mean anomalies for each MJO phase and season. For CHIRPS precipitation this included maps of three types of anomalies: daily, daily percentwise, and annual. For the variables used in the large-scale circulation analysis there are maps of only daily anomalies. Daily anomalies were computed as the difference between daily data and daily climatology, while daily percentwise anomalies were the percentage difference between daily data and monthly climatology (calculated as long-term means of the full data records). Note that daily percentwise anomalies were derived from monthly rather than daily climatology as the latter’s high variance can cause large swings in percentwise anomalies that obscure the overall trends we aim to study (particularly if a daily climatology value is near zero); we find the monthly climatology to be sufficiently stable over time to avoid this issue. Annual anomalies were computed from the daily anomalies, summing the latter for each year of the data record.

These three types of anomalies each provide a different perspective on the meteorological variables under study, and by considering them all we gain a more comprehensive physical understanding of the meteorology. Taking precipitation as an example, the daily anomalies convey in a direct physical sense (in units of mm day$^{-1}$) how daily precipitation deviates from what is expected based on climatology. However, this measure lacks valuable context regarding the magnitude of the underlying climatology: if a wet region and a dry region both receive the same amount of anomalous rainfall on a given day, the anomalous rainfall has a proportionally greater impact on the dry region. This missing climatological context is what is provided by the daily percentwise anomalies, which express anomalies as a percentage change relative to the (monthly) climatology.

Yet both the daily and daily percentwise anomalies are limited by their daily time scale: expressing daily anomalies as composites subdivided by season and MJO phase, as we do in this work, does not convey the impact of season length or of MJO phase frequency. For example, the southwest monsoon season (May–September) is about 2.5 times as long as the second intermonsoon season (October–November). So, even if daily precipitation anomaly composites were to be identical for the two seasons, the anomalies for the southwest monsoon season would be contributing 2.5 times as much anomalous rainfall over the course of a year. Analogously, MJO phase 3 (when defined based on OMI) occurs about 3 times as often as phase 5 during the second intermonsoon season (recall Table 1). To assess the impact of these differing season lengths and MJO phase frequencies, we use annual anomalies (in units of mm yr$^{-1}$). These anomalies are proportional to the daily anomalies, but scaled up by the mean number of days each combination of season and MJO phase occurs during a year.

The composite maps of CHIRPS rainfall anomalies include stippling to indicate statistical significance. This was determined using the nonparametric Mann–Whitney–Wilcoxon (MWW) test [also known as the Mann–Whitney $U$ test or the Wilcoxon rank-sum test, and implemented here using the R function wilcox.test()] (Mann and Whitney 1947; Wilcoxon 1945). The MWW test was used to assess whether the anomalies in a given season–phase combination differ significantly from all anomalies for said season, irrespective of phase. For more detail on similar use of the MWW test, see Recalde-Coronel et al. (2020).
Since this statistical scenario involves a collection of multiple individual tests (one statistical test per spatial grid cell), the significance of the MWW-generated p values cannot be interpreted on an individual basis by comparison to a predetermined test level (e.g., \( \alpha = 0.05 \)); with an increasing number of tests, there is a corresponding increase in the chance of erroneously rejecting at least one null hypothesis (i.e., incorrectly attributing significance to at least one grid cell’s anomaly). Wilks (2016) describes this problem in detail and also presents a solution for appropriately evaluating p value significance, the false detection rate (FDR) method. We use the FDR method in this work, wherein one specifies the control level for the false detection rate \( \alpha_{\text{FDR}} \); the expected fraction of grid cells that are erroneously reported as having statistically significant anomalies (i.e., erroneous rejection of the null hypothesis). One then computes a threshold of

![Composite maps of (CHIRPS v2.0) precipitation anomalies for Sri Lanka, subdivided by season (northeast monsoon, first intermonsoon, southwest monsoon, second intermonsoon) and OMI-based MJO phase (1–8). The number of days of data constituting each composite is indicated above each map. Stippling indicates statistical significance based on the Mann–Whitney–Wilcoxon test and the FDR method [described in section 2b(3)]. (left) Daily anomalies, calculated as the difference between daily data (for the given season–phase combination) and daily climatology (calculated from the full data record). (center) Daily percentwise anomalies, calculated as percentage differences between daily data and monthly climatology. The climatology used here is monthly rather than daily in order to minimize large swings in percentwise anomalies associated with small daily climatology values. (right) Annual anomalies, calculated as the annual sums of daily anomalies. These maps show different anomaly intensities compared to the daily anomaly maps because the number of days in each season–phase combination differs. Note that the same significance stippling is used here as for the daily anomalies.](image-url)


p value significance that is a function of \( \alpha_{FDR} \), the total number of grid cells, and the distribution of the \( p \) values when sorted in ascending order. This computed \( p \) value threshold is then compared to each grid cell’s \( p \) value to determine significance. In practice this threshold of \( p \) value significance is smaller than \( \alpha_{FDR} \), so the FDR test for a given value of \( \alpha_{FDR} \) is a stricter statistical test than individually testing each grid cell at the same numerical level, \( \alpha_0 = \alpha_{FDR} \). To be more precise, in this study we use an FDR control level of \( \alpha_{FDR} = 0.05 \), which attributes statistical significance to fewer grid cells than if each grid cell’s \( p \) value had been individually compared to \( \alpha_0 = 0.05 \).

4) PRECIPITATION FORECASTING POTENTIAL

HEAT MAPS

To explore the potential for MJO-informed subseasonal precipitation forecasts in Sri Lanka, we test a simple univariate, categorical forecast using a leave-one-year-out cross-validation scheme (as in Nardi et al. 2020; Baggett et al. 2018; Johnson et al. 2014; Mundhenk et al. 2018). This forecasting scheme is illustrated in detail in Fig. S4, so here we describe it in brief.

These forecasts consider the region of interest as a single unit, with precipitation anomalies being spatially averaged. For each combination of season and MJO phase we generated a set of rainfall forecasts, with one forecast for each strong MJO day (i.e., OMI amplitude \( \geq 1 \)) within the given season–phase combination. Each strong MJO day’s forecast is a binary prediction of either above-median or below-median precipitation based on comparison of two precipitation anomaly medians: the MJO-impact median—the median precipitation anomaly across all strong MJO days for the season–phase combination, except for the strong MJO days in the same year (i.e., “leave-one-year-out”)—and the baseline median, namely the median precipitation anomaly across the full historical record for that season (including all years and both weak and strong MJO days). If the MJO-impact median is greater (less) than the baseline median, we forecast above-median (below-median) precipitation for said season and year. The forecast is considered correct if the observed precipitation anomaly for the associated strong MJO day is also greater (less) than the baseline median. We repeated this analysis for a range of lead times (0–42 days).

We assessed forecasting accuracy for each season–phase–lead time combination using a variation of the Heidke skill score (HSS) with a baseline random forecast (e.g., Nardi et al. 2020; Baggett et al. 2018; Mundhenk et al. 2018):

\[
HSS = \left( \frac{C - E}{T - E} \right) \times 100,
\]

where \( T \) is the total number of forecasts, \( C \) is the number of correct forecasts, and \( E \) is the number of expected correct forecasts. Since our forecasts use the median as a reference level, a random forecast would be expected to be correct 50% of the time, so here \( E = T/2 \) and the HSS equation simplifies to

\[
HSS = \left( \frac{2C}{T} - 1 \right) \times 100.
\]

We determined the statistical significance of forecast skill for each season–phase–lead time combination with a one-tailed binomial test at the 95% confidence level, using a success probability of 0.5. This tests whether the number of correct forecasts for a given season–phase–lead time combination is significantly better than what could be achieved by a random (50/50) forecast.

3. Results and discussion

a. CHIRPS precipitation

Strong MJO-associated meteorological signals are evident in the composite maps of CHIRPS precipitation (Fig. 3). Precipitation anomalies are strongest in the SWM and SIM seasons, where they show a common pattern of peak enhanced precipitation during MJO phases 2–4 and peak suppressed precipitation during phases 6–8. This timing coincides with when the MJO region that is geographically closest to Sri Lanka is either its convectively active region of enhanced precipitation (phases 2 and 3) or its flanking region of suppressed precipitation (phases 6 and 7). The pattern differs somewhat in the other two seasons: during the NEM season there is not a strong suppressed precipitation signal in phase 7, and during the FIM season there is not a strong enhanced precipitation signal in phases 3 and 4. In fact, the precipitation anomaly pattern during the FIM season is offset by about one phase relative to the other seasons (e.g., anomalously dry in phases 5–7 rather than phases 6–8). These exceptions all correspond to variations in the MJO’s large-scale atmospheric circulation, as discussed later in this section.

The daily precipitation anomalies reflect the underlying spatial distribution of rainfall for each season (e.g., stronger signals in the southwest of the island during the SWM season) (recall Fig. 1). This spatial heterogeneity is muted in the daily percentwise anomalies in the majority of cases, suggesting that the MJO tends to alter rainfall across the island in proportion to the total amount of rain. Therefore while daily anomalies might appear small in drier regions of the island (e.g., the north and east during the SWM season), the magnitude of the corresponding daily percentwise anomalies indicates that these are still substantial deviations from the typical rainfall patterns in these regions. The annual anomalies highlight the tremendous strength of the MJO signal in the SIM season: there are large annual anomalies despite this season being one of the shortest. The annual anomalies also show the importance of the lengthy SWM season, which makes a substantial contribution to overall annual rainfall in Sri Lanka.

Given the notable differences in the precipitation anomalies across seasons, we will further discuss the patterns for each season individually.

1) NORTHEAST MONSOON (DECEMBER–FEBRUARY)

In the NEM season, daily anomalies of precipitation are strongest on Sri Lanka’s eastern side. This pattern corresponds to the season’s northeasterly monsoon winds bringing in moisture from the Bay of Bengal. There is a clear asymmetry between enhanced and suppressed precipitation across
phases, with more phases showing suppressed precipitation (primarily phases 5, 6, 8, and 1). The daily percentwise anomalies show a more uniform spatial distribution than the daily anomalies. Meanwhile the annual anomalies are fairly comparable to the daily anomalies.

Notably there is minimal signal in phase 7 across all three types of anomalies—despite both its neighboring phases (6 and 8) showing suppressed precipitation—which provides strong evidence that MJO impact in NEM phase 7 is negligible. This absence of a phase 7 signal is further considered in section 3b(1), where we show that during this phase the vertical pressure velocity anomalies over Sri Lanka (indicative of MJO-induced convection) are minimal.

2) FIRST INTERMONSOON (MARCH–APRIL)

The FIM season tends to have weaker daily anomalies than the other seasons, but there is still clear spatial heterogeneity where the strongest anomalies are in the southwestern part of the island and the weakest are to the north and east. In this season the phase-to-phase pattern appears “shifted back” by one phase relative to the patterns in other seasons, with enhanced precipitation in phases 8, 1, and 2 (and to some extent 3) and suppressed precipitation in phases 5–7. The daily percentwise anomalies are quite different from the daily anomalies; the strongest signals are in the coastal areas and eastern side of the island (particularly during phase 5), indicating that the MJO-associated anomalies in these regions represent substantial deviations from typical precipitation conditions. The annual anomalies show a severely attenuated version of the daily anomaly signal, indicative of the short length of this season.

3) SOUTHWEST MONSOON (MAY–SEPTEMBER)

The SWM season has strong daily anomaly signals focused in phases 2–4 (enhanced precipitation) and phases 6–8 (suppressed precipitation). The other phases, 1 and 5, are transitional phases with minimal signal. Barring these transitional phases, the anomaly signal is strongest in the southwest part of the island and weakest in the north and east. This pattern corresponds to the season’s southwesterly monsoon winds, which bring in moisture from the equatorial Indian Ocean and then break upon reaching the higher topography of the central highlands. The patterns for phases 2–4 versus phases 6–8 are remarkably symmetric, both in absolute intensity and spatial extent.

Although the daily percentwise anomalies broadly show the same phase-to-phase patterns as the daily anomalies (strong enhanced precipitation in phases 2–4, strong suppressed precipitation in phases 6–8, transitional phases 1 and 5), the spatial patterns are dramatically different. In particular, there is a tendency in phases 3, 4, 7, and 8 for the larger relative changes to be found in the north and east (i.e., the leeward side of the central highlands). These regions are drier at this time of year, so even small daily anomalies represent notable (percentwise) deviations from typical precipitation.

The annual anomalies for the SWM season stand out relative to the other seasons. This is understandable since the SWM season is by far the longest, representing five months of the year. We also see phase-to-phase differences in these annual anomalies, with anomalies stronger in phases 2 and 3 than in 4. Similarly, we see a stronger signal in phases 6 and 7 than in 8. This differs from the daily anomalies, where anomalies were fairly comparable in magnitude across these six phases. These phase-to-phase differences are attributable to seasonal variation in the frequency of each MJO phase: during the SWM season there are more days of MJO phases 2, 3, 6, and 7 and fewer days of phases 1, 4, 5, and 8 (recall Table 1). The annual anomalies take this phase frequency into account, whereas the daily anomalies do not.

4) SECOND INTERMONSOON (OCTOBER–NOVEMBER)

The SIM season is broadly similar to the SWM season in that it also has strongly enhanced precipitation in phases 2–4, strongly suppressed precipitation in phases 6–8, and transitional phases 1 and 5. However daily anomalies for this season show a distinct spatial pattern: during phase 2 the strongest signal is in the southwest of the island, by phase 3 there is also a similarly strong signal across the north and east, and by phase 4 the strongest signal is solely in the north and east. This progression from phase 2 to 4 is mirrored in phases 6–8.

The daily percentwise anomalies are similar to those for the SWM season in that phases 3, 4, and 6–8 show a stronger signal in the north and east, away from the high topography of the central highlands. The MJO thus changes both the spatial pattern and magnitude of precipitation.

The annual anomalies are notable despite the SIM season’s short two-month length. We see a stronger signal in phases 6 and 7 than in phase 8 (as opposed to a strong signal throughout 6–8 as in the daily anomalies). This is similar to the SWM season, and we can similarly attribute this to seasonal variation in MJO phase frequency: during the SIM season there are more days of MJO phases 2, 3, 6, and 7 and fewer days of phases 1, 4, 5, and 8 (Table 1).

5) SENSITIVITY TO MJO INDEX AND PRECIPITATION DATASET

While the results presented thus far use OMI-based phases, it is important to highlight the differences that arise when defining phases based on RMM, which is the more frequently used MJO index in the literature. Although the precipitation patterns in the FIM and SWM seasons are comparable for OMI- and RMM-based phases, the patterns differ in the NEM and SIM seasons (Fig. S2). In the NEM season, RMM yields small anomaly signals in phases 1 and 8 and notably suppressed precipitation in phase 7, such that the suppressed precipitation phases are 5–7 (rather than OMI’s suppressed phases 5, 6, and 8). In the SIM season RMM yields anomaly patterns shifted by one phase relative to OMI, such that enhanced precipitation occurs in phases 1–3 and suppressed precipitation in phases 5–7. This one-phase discrepancy may be explained by the temporal offset between OMI- and RMM-based phases; Kiladis et al. (2014) notes that, for September–November, OMI-based phases lead RMM-based phases by about four days (i.e., approximately the duration of one MJO
phase). Therefore, the same SIM days are categorized as two different (but neighboring) MJO phases by OMI versus RMM, which can explain the one-phase offset in SIM precipitation between the two MJO indices.

Another point of comparison for our results is station-based data. A comparable analysis of MJO impact on Sri Lankan rainfall has been done by Jayawardena et al. (2020), who studied both station rainfall data and CHIRPS precipitation (although they presented only station data due to similar results between the two). Our CHIRPS data subdivided by RMM-based phases (Fig. S2) are fairly comparable to their station-based data, which also use RMM. Meanwhile our CHIRPS data subdivided by OMI-based phase (Fig. 3) noticeably differ, particularly in the second intermonsoon season where the anomaly pattern is offset by one phase.

Given the similarity between station data and our CHIRPS data when they are both subdivided by RMM-based phase, it seems that differences in the CHIRPS data subdivided by OMI-based phases are mostly attributable to the choice of MJO index: RMM versus OMI. This highlights the importance of which MJO index is used, which must be considered when interpreting results specifying particular MJO phases. For example, our finding of an enhanced precipitation pattern in phases 2–4 during the SIM season is inseparably linked to the fact that these are OMI-based phases; if using RMM. Meanwhile our CHIRPS data subdivided by OMI-based phase (Fig. 3) noticeably differ, particularly in the second intermonsoon season where the anomaly pattern is offset by one phase.

b. Large-scale MJO behavior

Since the CHIRPS MJO precipitation anomalies show strong MJO-associated signals, it is prudent to investigate the concurrent large-scale behavior of the MJO (i.e., the location and strength of the MJO’s convectively active and suppressed regions). How does this large-scale behavior correspond to the observed local precipitation anomalies over Sri Lanka? To investigate this large-scale MJO behavior we use ERA5 reanalysis data, which, unlike the land-restricted CHIRPS dataset, span both the island of Sri Lanka and the surrounding Indian Ocean. Although ERA5’s spatial resolution is coarser than that of CHIRPS (0.25° vs 0.05°) and does not necessarily capture small-scale interactions that may be important for Sri Lanka, observing broad patterns (such as the spatial overlap between Sri Lanka and the MJO’s convective anomalies) leads us to a better understanding of the mechanism of MJO influence on Sri Lanka. A caveat of using ERA5 here is that reanalysis products typically have significant uncertainties, and ERA5 in particular tends to have a wet bias in daily precipitation [recall the discussion in section 2a(1)]. While we use ERA5 since it, unlike many other gridded products, covers our timespan, region, and variables of interest at sufficient spatiotemporal resolution, its inherent limitations must be kept in mind when considering our interpretations of the data.

For this large-scale analysis we consider not only ERA5 precipitation, but a suite of other atmospheric fields where we expect the MJO to manifest as anomalous spatial patterns: outgoing longwave radiation (OLR) at the top of the atmosphere, specific humidity at 500 hPa, vertical pressure velocity (ω) at 500 hPa, and horizontal winds at 850 hPa (lower troposphere) and 250 hPa (upper troposphere). The convectively active region (i.e., enhanced precipitation) is indicated by negative anomalies in OLR due to greater abundance of convective clouds, as well as by negative anomalies in 500-hPa (midtropospheric) ω indicating convection. This is accompanied by positive anomalies in 500-hPa (midtropospheric) specific humidity [conducive to and associated with deep convection, per Natoli and Maloney (2019), Bretherton et al. (2004), Holloway and Neelin (2009, 2010), Yuan and Houze (2013), and Gray (1979)], converging 850-hPa winds, and diverging 250-hPa winds (e.g., Zhang 2005; Rui and Wang 1990). Meanwhile the MJO’s convectively suppressed region (i.e., suppressed precipitation) is indicated in each field by the opposite signal: positive anomalies in OLR and ω, negative anomalies in specific humidity, diverging 850-hPa winds, and converging 250-hPa winds. For each of these fields we generated season–phase composites of daily anomalies (Figs. 4–7 and Figs. S5–S8). Since each season-phase composite represents a different number of days of data (ranging from 84 days for SIM phase 5 to 528 days for SWM phase 2, per Fig. 3), we may expect greater variance in anomaly magnitudes for season–phase combinations with fewer days of data. We have not quantified this variance as we focus on the broad patterns of these anomalies rather than on their precise values, so we caution against any interpretations of Figs. 4–7 that may be sensitive to this limitation.

The season–phase composites generally show strong anomalies that are characteristic of the MJO, matching the eastward propagation of its convectively active region and suppressed region near Sri Lanka (Figs. 4–7). Importantly, we see general agreement between ERA5 precipitation and the CHIRPS precipitation discussed in the previous section: although the coarser resolution of ERA5 precipitation misses much of the spatial heterogeneity observed in the CHIRPS data, the two datasets tend to match in terms of the sign of precipitation anomalies in each season and phase. However, the other ERA5 meteorological fields show that the MJO-associated anomalies can exhibit slightly different patterns from one field to another [e.g., anomalies in OLR and ω match in sign, but are not necessarily congruent in magnitude or spatial extent, such as in MJO phase 7 of the FIM season (Fig. 5)]. This means that each field can interact with the small-scale topography of Sri Lanka in different ways.

There are substantial seasonal differences in these large-scale ERA5 signals—discussed in detail in the subsequent sections—that help explain the seasonal variation in MJO-associated CHIRPS precipitation over Sri Lanka (recall Fig. 3). In general, enhanced precipitation occurs when the MJO’s convectively active region is close to Sri Lanka (as indicated by the large-scale meteorological anomalies), suppressed precipitation occurs due to proximity of the MJO’s suppressed region, and minimal precipitation anomalies occur when neither the convectively active region nor the suppressed region is closer to Sri Lanka. For example, we noted that the FIM season’s CHIRPS precipitation pattern is offset by about 1–2 phases relative to the other seasons (Fig. 3), and
FIG. 4. Composite maps of (ERA5) anomalous atmospheric fields during the northeast monsoon season (December–February), subdivided by OMI-based MJO phase. The mapped variables are (column 1) precipitation and 850-hPa (lower troposphere) winds, (column 2) outgoing longwave radiation (OLR) and 250-hPa (upper troposphere) winds, (column 3) 500-hPa specific humidity, and (column 4) 500-hPa vertical pressure velocity ($v$). Wind anomalies weaker than 1 m s$^{-1}$ are omitted for clarity. These composites are all generated from daily anomalies, calculated as the difference between daily data (for the given season–phase combination) and daily climatology (calculated from the full data record).
this aligns with a similar phase shift in large-scale MJO behavior (as indicated by ERA5 anomalies) during the FIM season (Fig. 5). Similarly, large-scale behavior helps explain the noticeably weak precipitation anomaly signals during phase 7 in the NEM season and during phases 3 and 4 in the FIM season, despite these phases being associated with strong signals in other seasons. This correspondence—between the large-scale meteorological patterns of the MJO and the local MJO-associated precipitation anomalies in Sri Lanka—provides further evidence for the MJO having a direct impact on Sri Lankan precipitation according to the proximity of its convectively active region or suppressed region.

![Fig. 5. As in Fig. 4, but for the first intermonsoon season (March–April).](image-url)
However, there is nuance to this correspondence between large-scale atmospheric conditions and precipitation: the spatial patterns of the ERA5 precipitation anomalies within Sri Lanka are more closely associated with anomalies in 500-hPa $v$ than in OLR or 500-hPa specific humidity. The close association between precipitation and 500-hPa $v$ anomalies is expected since ERA5 precipitation is based on physical parameterizations rather than data assimilation (and is therefore a function of $\omega$) (ECMWF 2016). The lower association between precipitation and OLR anomalies aligns with what we know of MJO impacts on the islands of the Maritime Continent. There, OLR does not act as a good proxy of the MJO-associated precipitation over land (Peatman et al. 2014). This may be because OLR is essentially a measure of cloud-top height: it is sensitive to the deep
convection of the MJO’s convectively active region, but it is less effective at capturing the low-level convection characteristic of other MJO-associated rainfall mechanisms (e.g., orographic lift and modulation of the diurnal rainfall cycle).

In the subsequent sections we discuss the large-scale atmospheric patterns for each season, with a particular focus on how these patterns correspond to local precipitation anomalies in Sri Lanka (as seen in Fig. 3). A note on the maps to follow (Figs. 4–7): although the MJO is a global-scale phenomenon, these maps focus on a smaller region around Sri Lanka so as to highlight associations between Sri Lankan rainfall and the large-scale meteorological patterns. This comes at the expense

<table>
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<tr>
<th>Phase</th>
<th>Precipitation (850-hPa winds)</th>
<th>OLR (250-hPa winds)</th>
<th>Specific humidity @ 500 hPa</th>
<th>Vert. pressure velocity @ 500 hPa</th>
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**Fig. 7.** As in Fig. 4, but for the second intermonsoon season (October–November).
of seeing broader patterns of MJO-associated meteorology for each season and phase, so we have included complementary figures showing a larger region of the Indian Ocean in the supplemental material (Figs. S5–S8).

1) NORTHEAST MONSOON (DECEMBER–FEBRUARY)

Precipitation variability in this season seems most closely associated with variations in $\omega$ (i.e., large-scale vertical ascent). In phase 1 Sri Lanka is between the MJO’s convectively active region (the spatially coherent anomalies in the western Indian Ocean in Fig. S5) and suppressed region (the anomalies of opposite sign over the Maritime Continent). This in-between state would suggest minimal MJO-associated precipitation anomalies during this phase—which is in fact the case for ERA5 precipitation (Fig. 4)—yet there are definitively negative anomalies in eastern Sri Lanka in the higher-resolution CHIRPS precipitation (Fig. 3). The closest link between the CHIRPS anomaly pattern and ERA5 data appears to be in the positive $\omega$ anomaly across the southeast of the island. This anomaly appears to be associated with the MJO’s suppressed region, the bulk of which lies farther east (Fig. S5). Yet this disjointed remnant still lingers over Sri Lanka in phase 1, just before the convectively active region moves in from the west and expands northward in subsequent phases. In phases 2–4 the convectively active region has moved over Sri Lanka—with a particularly strong island-wide signal in all fields during phase 3—which corresponds closely to the enhanced CHIRPS precipitation during these phases (Fig. 4). Phases 5–8 then have the MJO’s suppressed region over Sri Lanka, which explains the negative CHIRPS precipitation anomalies in phases 5, 6, and 8. Phase 7, however, has a minimal CHIRPS (and ERA5) precipitation anomaly signal. Why phase 7 would be an exception is not immediately clear from the OLR and specific humidity fields, which lie over Sri Lanka. However, we do find some association in the $\omega$ field, which shows a weaker signal over Sri Lanka during phase 7 than during phases 5, 6, and 8.

2) FIRST INTERMONSOON (MARCH–APRIL)

In the FIM season, as in the NEM season, precipitation anomaly patterns appear to align closely with anomalies in $\omega$. However, here we see a different CHIRPS precipitation anomaly pattern than in the other seasons, with enhanced precipitation in phases 8, 1, and 2 (rather than 2–4) and suppressed precipitation in phases 5–7 (rather than 6–8) (Fig. 3). During phases 1 and 2 the convectively active region is located over Sri Lanka, corresponding to the enhanced precipitation during these phases. Phases 3 and 4 still show OLR and specific humidity anomalies close to Sri Lanka that are indicative of the convectively active region, yet precipitation $\omega$ anomalies in these phases are weak over the island (Fig. 5). This lack of precipitation signal may be a result of the expansive region of anticyclonic wind anomalies, anomalously positive OLR, negative specific humidity, and positive $\omega$ that lies ~20° north of Sri Lanka during these phases, possibly associated with Rossby wave propagation northwest of the MJO’s convectively active region (Fig. S6). This northern pattern, characteristic of subsidence and drier conditions, may be counteracting the enhanced precipitation effects of the MJO’s convectively active region. This northern anomaly region is present in phases 7–8 as well (but with opposite sign).

Phases 5–7 show the MJO’s suppressed region encompassing Sri Lanka, matching the concurrent suppression of precipitation. In phase 8 there are minimal large-scale anomalies over Sri Lanka, suggesting that neither the MJO’s convectively active region nor its suppressed region are near the island at this time. Yet there is enhanced precipitation in both the ERA5 data (Fig. 5) and the CHIRPS data, including large percentile anomalies in eastern Sri Lanka (Fig. 3). Scrutinizing the ERA5 nonprecipitation fields with this in mind, there exist corresponding indications of enhanced precipitation. For one, there is a simultaneous convective signal over Sri Lanka in the ERA5 $\omega$ field (Fig. 5). The 850-hPa winds may also play a role here; there seems to be an association between easterly (westerly) 850-hPa wind anomalies and enhanced (suppressed) precipitation, and in phase 8 the wind anomalies are easterly. So while there do exist anomalies in atmospheric conditions that are conducive to enhanced precipitation, they are not clearly associated with the MJO’s convectively active and suppressed regions. The reason for this discrepancy is unclear, although one possibility is that the weak outer edge of the convectively active region is in fact over Sri Lanka at this time, but is not apparent in Fig. 5 due to small-scale variability in magnitude (preventing the lower-resolution ERA5 from clearly resolving its features).

3) SOUTHWEST MONSOON (MAY–SEPTEMBER)

In the SWM season, precipitation anomalies are not quite as closely coupled to the spatial patterns of $\omega$ anomalies as was observed for the NEM and FIM seasons (Fig. 6). In particular, $\omega$ anomalies show a strong standing wave pattern over the central highlands—most noticeably during phases 1 and 5—that is associated with strong 850-hPa winds and lower specific humidity. Also, strong signals in all the meteorological fields are shifted northward relative to the same signals in the NEM and FIM seasons (Fig. S7). This is consistent with the off-equator propagation of the intraseasonal oscillation (i.e., BSISO as opposed to classic MJO) in the boreal summer season. In phase 1 the suppressed region extends farther westward such that Sri Lanka lies between it and the convectively active region. This neatly corroborates our assessment of phase 1 as a transitional phase due to its minimal CHIRPS precipitation anomalies. In phases 2–4 the convectively active region is located over Sri Lanka, corresponding to the enhanced precipitation anomalies during these phases. A rain shadow effect is seen in the precipitation and $\omega$ anomalies, not only in the eastern region of Sri Lanka leeward of the central highlands, but also in the northern region of Sri Lanka that is leeward of the Western Ghats of southern India (Fig. 6). In phase 5 (the other transitional phase) Sri Lanka is located between the convectively active region and the suppressed region in the western Indian Ocean. Phases 6–8 have the MJO’s suppressed region encompassing Sri Lanka, corresponding to the suppression of precipitation during these phases. The precipitation and $\omega$
anomalies mirror the rain shadow effect seen in phases 2–4, albeit with opposite sign.

4) SECOND INTERMONSOON (OCTOBER–NOVEMBER)

The large-scale patterns in the SIM season (Fig. 7) have more similarity to the SWM season than to the NEM or FIM seasons. As in the SWM season, the large-scale meteorological signals are shifted northward relative to the same signals in the NEM and FIM seasons (Fig. S8). Unlike the SWM season, the ERA5 precipitation anomalies are closely associated with the spatial patterns of ω (as in NEM and FIM). However, there is some disagreement between ERA5 (Fig. 7) and CHIRPS precipitation (Fig. 3), with ERA5 not fully capturing the intensity of the CHIRPS precipitation anomalies in eastern Sri Lanka.

In phase 1 Sri Lanka is at the edge of the MJO’s suppressed region (Fig. S8). However, this precipitation-suppressing influence is presumably counterbalanced by the proximity of the strong convectively active region and the strong onshore winds (both associated with enhanced precipitation), yielding the minimal CHIRPS precipitation anomalies of this transitional phase (Fig. 3). During phases 2–4 the convectively active region encompasses Sri Lanka—with exceptionally strong signals in all ERA5 meteorological fields (Fig. 7)—explaining the enhanced CHIRPS precipitation anomalies in these phases (Fig. 3). In phase 5 Sri Lanka is still at the edge of the convectively active region, but the strong suppressed region is nearby. This is analogous to phase 1 but with the locations of the convectively active region and the suppressed region reversed, and it similarly corresponds to minimal precipitation anomalies during this transitional phase. The ω anomaly field shows a hint of the standing wave pattern over the central highlands that was evident in the SWM season. In phases 6–8 the suppressed region signal is located over Sri Lanka, aligning with the suppression of precipitation in these phases.

c. Diurnal patterns of MJO influence

As discussed in the previous section, the large-scale daily anomalies of ERA5 meteorological variables show a fairly direct MJO impact on Sri Lankan rainfall: local rainfall anomalies correspond to proximity of the MJO’s convectively active or suppressed region. While this result is straightforward and at first glance seems obvious, this manner of MJO influence differs from that found in islands of the (more widely studied) Maritime Continent, which experience MJO-associated rainfall anomalies before the arrival of the convectively active and suppressed regions (e.g., Wang and Sobel 2017; Qian 2020; Natoli and Maloney 2019). In studies of rainfall associated with the MJO’s convectively active region, enhanced rainfall occurred with a lead time of about one week or one MJO phase (e.g., Peatman et al. 2014; Ichikawa and Yasunari 2006, 2008; Wu and Hsu 2009; Natoli and Walsh 2011, 2013; Vincent and Lane 2016; Zhang and Ling 2017), with a stronger signal in coastal areas than in the interiors of large islands (Sakaeda et al. 2017). This early rainfall signal is attributed to the MJO-associated wind and shortwave radiation anomalies that precede the convectively active and suppressed regions, enhancing or suppressing the typical land–sea breeze and associated diurnal rainfall cycle. Given that the MJO’s impact in these other settings is partially mediated by the diurnal rainfall cycle, here we consider MJO-associated variability in Sri Lanka’s diurnal rainfall cycle across seasons and MJO phases.

We consider the MJO’s impact on diurnal rainfall cycle not only for Sri Lanka as a whole, but also for four regions of the island chosen to represent a range of climatic zones with varying seasonality: the northern coast, eastern coast, central highlands, and southwestern coast (Fig. 8). Note that the bounding boxes used to isolate these regions and Sri Lanka as a whole also encompass some amount of coastal ocean. Therefore the diurnal rainfall curves shown in Fig. 8 contain some oceanic contribution [with the nighttime rainfall peaks perhaps being analogous to the offshore nocturnal rainfall maxima observed for the islands of the Maritime Continent (Bai et al. 2021)]. An important caveat to this analysis arises from our use of ERA5 hourly precipitation. While we use ERA5 since its long record can match the span of our other analyses (1981–2020), studies of other regions have noted that ERA5 has difficulty in reproducing aspects of diurnal precipitation cycle such as peak time and magnitude (Tang et al. 2020; Hong et al. 2021; Gao et al. 2020; Kumar et al. 2021; Hayden et al. 2023). To consider how this ERA5 uncertainty influences our interpretation of MJO impact, we compared hourly precipitation from ERA5 and IMERG—a satellite-based product that, per the same studies, more accurately represents the diurnal cycle—over their shared temporal range of 2001–20 (Figs. S9 and S10, which are analogous to Fig. 8). Compared to IMERG, the ERA5 diurnal cycles sometimes differ in magnitude and (to a lesser extent) qualitative shape. Moreover, the time of peak ERA5 precipitation tends to occur an hour or two before the IMERG peak. Despite these differences, there are two MJO-relevant aspects of the diurnal cycle that are generally consistent between ERA5 and IMERG (Figs. S9 and S10) and between ERA5 time ranges (Fig. 8 and Fig. S9), lending confidence to their robustness: 1) MJO modulation takes the form of enhancing/suppressing the mean diurnal cycle (i.e., the MJO typically does not change the qualitative shape of the diurnal rainfall curve), and 2) the MJO phase timing of greatest (least) peak rainfall corresponds to the proximity of the MJO’s convectively active (suppressed) region, indicating a direct MJO impact on rainfall (e.g., during the SWM season the diurnal cycle’s magnitude is greatest for MJO phases 2–4). These modulations are dependent on both season and on region, the nuances of which we now describe.

When considering all of Sri Lanka in aggregate (top row of Fig. 8) the diurnal rainfall cycle is similar across seasons: it has two peaks, a primary one in the afternoon and a secondary one at night, and this bimodal shape is preserved across seasons (albeit with shifts in magnitude of rainfall). The MJO modulates this diurnal cycle by enhancing or suppressing rainfall at all hours of the day, shifting this entire curve higher or lower. The MJO phases at which rainfall is highest or lowest mirror the patterns in the CHIRPS data (Fig. 3). For example, during the SWM season, highest rainfall is during phases 2 and 3 while lowest is during phases 6 and 7.
The eastern and northern coasts have notable rainfall outside of the afternoon peak, with a second, nighttime peak present in most seasons as well (the only exception being the eastern coast in the SWM season, when this region is in the rain shadow of the central highlands and thus almost all rainfall is concentrated in the afternoon peak). In terms of MJO influence, the diurnal cycle varies substantially with MJO phase. For example, instead of the afternoon peak only changing in magnitude from MJO phase to phase, it also changes in time of day (e.g., for the eastern coast during the NEM, the afternoon peak is at 1330 during MJO phase 2, but at 1630 during MJO phase 5).

The central highlands and southwestern coast have diurnal cycles similar to the all-island cycle, with a single primary rainfall peak in the afternoon. In most seasons there is minimal rainfall at other times of day so the MJO-associated rainfall influence is primarily via amplification or suppression of this peak. However, in the SWM and SIM seasons the southwestern coast receives rainfall at all times of day (on average), and all of this rainfall is modulated by the MJO. This seasonal difference is attributable to the prevailing winds during the SWM and SIM seasons and their interaction with the southwestern coast; the southwesterly monsoon winds dominate at this time, bringing moisture from the Indian Ocean to the southwestern coast and facilitating rainfall outside of the typical afternoon peak.

The regional diurnal cycles generally match the all-island cycles in terms of the MJO phase timing of greatest and least peak rainfall (e.g., the diurnal rainfall curves in the FIM season have the largest afternoon peaks in phases 8, 1, and 2). This indicates a direct impact of the MJO, where the positive (negative) rainfall anomalies are maximal when the convectively

![Figure 8. Time series of the mean diurnal precipitation cycle for each season and OMI-based MJO phase (from hourly ERA5 data for 1981–2020). In each plot the thicker black line shows the mean diurnal cycle for the season as a whole, while the colored lines show the mean diurnal cycle for a given MJO phase within the season. The first row shows the mean diurnal cycle within a bounding box surrounding the entire island (region A on the inset elevation map), while the subsequent rows correspond to mean diurnal cycles when spatially averaging over smaller, climatically distinct regions of Sri Lanka: northern coast (region B), eastern coast (region C), central highlands (region D), and southwestern coast (region E).]
active (suppressed) region is closest to Sri Lanka (akin to our findings from sections 3a and 3b). This differs from the mechanism of MJO impact at play in the islands of the Maritime Continent, where there is some degree of MJO rainfall influence prior to the arrival of the convectively active region due to the wind and shortwave radiation anomalies that precede it. In summary, while the diurnal rainfall cycles in all of these regions of Sri Lanka are clearly modulated by the MJO, the phase timing of this modulation suggests that the sea breeze–associated mechanism of MJO impact for the islands of the Maritime Continent is not a primary mechanism of MJO impact in Sri Lanka.

d. Precipitation forecasting potential

Thus far we have identified strong MJO-associated precipitation anomalies over Sri Lanka. Given the systematic patterns of these anomalies, we now consider the possibility of forecasting rainfall based on MJO state. Namely, if we know the present phase of the MJO, how well can we predict rainfall for the next few weeks?

To investigate this question we generated a set of forecasts for each combination of season, OMI-based MJO phase (1–8), and lead time (0–42 days). We assessed forecasting skill using Heidke skill scores (HSS) and generated heat maps of these scores as in Nardi et al. (2020) (Figs. 9–11). On these heat maps the hue of each cell indicates the direction of the forecast (blue-green for above-median rainfall, brown for below-median rainfall), with darker colors indicating higher skill. Useful reference values for interpreting HSS are 100 (all correct forecasts), 0 (50% correct; i.e., no better or worse than random forecasts), and 30 (65% correct, or approximately twice as many correct as incorrect forecasts) (Nardi et al. 2020). Details on this binary forecasting scheme and the HSS formula used in this study can be found in section 2b(4) and the references therein.

Here we focus on forecasts based on unfiltered data. Although forecasts based on filtered data show much higher HSS values (Fig. S11), unfiltered data are of greater relevance for forecasting applications since filtering (as applied here) is a lossy process—the filtering in this study results in the loss of 100 days of data at both the beginning and end of the data record—which makes it impractical for real-time forecasting.

Given the substantial regional variability of precipitation (Figs. 3 and 8), we generated these forecasts not only for the entire island of Sri Lanka spatially aggregated as one unit, but also for the four smaller regions analyzed in the previous section (Fig. 8): northern coast, eastern coast, central highlands, and southwestern coast. For brevity we only show the heat maps for the entire island and for two regions with distinct patterns in skill: the southwestern coast and the eastern coast. The other two heat maps can be found in supplemental material (Figs. S12 and S13).

First, in looking at the all-island heat map (Fig. 9), we find systematic patterns of phase–lead time combinations for which the HSS values indicate significant skill for predicting above-median versus below-median rainfall. The SIM season has phase–lead time combinations with greatest forecast skill (highest HSS values), while the SWM season has the greatest number of phase–lead time combinations with statistically
significant skill (~270 phase–lead time combinations versus SIM’s ~200). The FIM season has somewhat weaker skill than SIM and SWM, neither having as many high HSS values as in SIM nor having as many phase–lead time combinations with significant skill as in SWM. However, in the FIM season there is significant skill at ~39–42 days for phases 1–3, a regime where the SIM season has no significant skill. The NEM season notably has the lowest skill, with faint patterns across the HSS heat map that are barely reminiscent of the well-defined diagonal patterns visible for the other seasons.

The forecasts with a lead time of zero days generally corroborate the precipitation anomaly patterns of the composite maps (recall Fig. 3). The forecasts at nonzero lead times show systematic patterns of alternating significant and nonsignificant skill with increasing lead time. This yields some forecasts with strong predictive skill even at long lead times, presumably due to the regularity with which the MJO transitions through its eight phases (approximately 4–8 days per phase given a typical MJO life cycle of 30–60 days). Taking the SIM season’s phase 1 as an example, there is nonsignificant forecasting skill at zero lead time (reflecting the fact that

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**Region C: Eastern Coast**

- **Northeast Monsoon (Dec–Feb)**
- **First Intermonsoon (Mar–Apr)**
- **Southwest Monsoon (May–Sep)**
- **Second Intermonsoon (Oct–Nov)**

**HSS**

100 40 30 20 10 0 10 20 30 40 100

**FIG. 10.** As in Fig. 9, but for the eastern coast region (see Fig. 8 for region boundaries).

**Region E: Southwestern Coast**

- **Northeast Monsoon (Dec–Feb)**
- **First Intermonsoon (Mar–Apr)**
- **Southwest Monsoon (May–Sep)**
- **Second Intermonsoon (Oct–Nov)**

**HSS**

100 40 30 20 10 0 10 20 30 40 100

**FIG. 11.** As in Fig. 9, but for the southwestern coast region (see Fig. 8 for region boundaries).
anomalies in this phase are small; Fig. 3). Yet there is significant forecasting skill in predicting enhanced rainfall 3–24 days after phase 1, corresponding to the MJO’s transition into the enhanced rainfall phases 2–4. This is followed by nonsignificant forecasting skill 25–29 days after phase 1, corresponding to phase 5’s minimal rainfall anomalies. Then 30–39 days after phase 1 there is significant forecasting skill in predicting suppressed rainfall, corresponding to the MJO’s transition into the suppressed rainfall phases 6–8. The last few days, 40–42 days after phase 1, have nonsignificant skill, indicating the completion of the MJO cycle and a return to phase 1’s minimal rainfall anomalies. The reliable phase transitions of the MJO are what yield the characteristic diagonal patterns of the HSS heat maps, with the slope of these patterns interpretable as the speed with which the MJO transitions from phase to phase.

In comparing these OMI-based forecasts to RMM-based ones (Fig. S14) we find that OMI-based forecasts tend to have higher skill in all seasons. This result is expected for the SWM (May–September) and SIM (October–November) seasons, as these seasons are when one would expect the OMI to capture subseasonal variability better than the RMM (i.e., when the dominant subseasonal variability mode is the BSISO, which the OMI is designed to capture) (Kikuchi et al. 2012). It is less expected and quite interesting to see that OMI provides higher forecast skill in the other two seasons as well. This all-season improvement suggests that, in the context of generating skillful MJO-informed precipitation forecasts for Sri Lanka, the OMI may be preferable to the widely used RMM.

Given Sri Lanka’s various climatic zones (recall Fig. 1), it is sensible to also focus this forecasting scheme on specific regions of Sri Lanka with distinct rainfall patterns rather than only considering the island as a single aggregate unit.

The eastern coast’s heat map (Fig. 10), for example, is quite different from the all-island heat map, indicating that a regionally customized forecast system could be of value in this area. Yet there is lower skill in all seasons compared to the all-island heat map, even for the NEM season during which the eastern coast experiences strong MJO-associated rainfall anomalies (Fig. 3), which points to the challenge of establishing actionable forecasts targeted for specific regions within Sri Lanka.

The southwestern coast’s heat map of forecasting skill (Fig. 11) is highly similar to the all-island heat map. However, skill is slightly lower than for the all-island forecasts (both in terms of lower HSS values and fewer significant forecasts), even in the SWM and SIM seasons during which the southwestern coast experiences the strongest MJO-associated rainfall anomalies (Fig. 3). This is interesting given that not all regions show the same predictability patterns, which might be expected to drive down the skill of all-island forecasts.

The results of this regional forecasting lead us to the major point—consistently arising throughout this paper—that Sri Lanka is a climatically diverse island with substantial regional climate variability. The heat map patterns of significant forecasts can differ substantially from region to region. For example, for the southwestern coast, phase 3, at 14-day lead time, there is a significant forecast of below-median rainfall. For the same season–phase–lead time combination on the eastern coast, there is a significant forecast of opposite sign (above-median rainfall).

In thinking beyond the simple forecasting scheme implemented here and toward applied forecasting, these regional climatic variations are critical: forecasts of local conditions are more actionable than forecasts of countrywide mean conditions when considering major impacts of rainfall variability in Sri Lanka, such as losses in agricultural yield, reductions in hydropower generation, and modulation of mosquito-borne disease incidence (Jayawardena et al. 2022). Extension of this MJO-informed forecasting work also requires careful consideration of the lead times at which forecasts are valuable, which is application specific. This is particularly relevant given the forecasting patterns observed here: significant skill alternating with nonsignificant skill for varying lead times, presenting systematic stretches of time when forecast skill is minimal. Finally, this forecast scheme is limited by its binary categorization: we have predicted rainfall as either above or below median, but how much above or below? The magnitude of the rainfall anomaly is a critical parameter, and could be explored with an increase in complexity of the forecasting scheme, such as by introducing more categories for the forecasted rainfall (e.g., “greatly above median”, “near median”, “greatly below median”).

4. Conclusions

The goals of this study were to describe MJO influence on Sri Lankan precipitation across seasons, understand mechanisms of this influence, and explore potential for MJO-informed subseasonal forecasts. In examining these relationships we find first-order similarity across seasons, with MJO influencing Sri Lankan precipitation by direct propagation of the MJO convectively active region and suppressed region over the island (as opposed to the temporally leading influence seen in another tropical setting: the islands of the Maritime Continent). There are, however, meaningful differences among seasons in the strength of these relationships and, in some cases, the exact phasing of the relationships. We find, for example, that the magnitude of precipitation anomalies does not always match the timing of greatest atmospheric anomalies. We also find a notable phase offset in the FIM season that appears to relate to Rossby wave circulation features over the Indian subcontinent. These findings generally corroborate those of Jayawardena et al. (2020) while expanding on their work by exploring the nuances of MJO characterization (using temporal filtering and considering OMI versus RMM indices) and by considering another perspective on MJO influence: its impact on the diurnal rainfall cycle.

Importantly, we find significant associations between MJO and Sri Lankan precipitation at time scales up to several weeks, which may have implications for MJO-informed rainfall forecasting. These associations are generally stronger when using OMI-based phases rather than RMM-based ones, suggesting that OMI may be the more useful metric for such applications. These associations also differ from region to region within Sri Lanka, highlighting the climatic heterogeneity of the island. However, we have found these results using a
highly simplified approach to forecasting: we have not considered the magnitude of deviation from median rainfall, nor the intensity of the MJO. We also have not considered any covariates such as the state of El Niño–Southern Oscillation, which not only influences seasonal rainfall in Sri Lanka (e.g., Abeysekera et al. 2019; Malmgren et al. 2003; Zubair et al. 2008; Suppiah 1997; Zubair and Ropelewski 2006) but also modulates MJO characteristics such as intensity, propagation speed, and phase frequencies (e.g., Pang et al. 2016; Zaitchik 2017; Vashisht and Zaitchik 2022). Moreover, even demonstrated rainfall forecast skill is not sufficient to demonstrate utility.

In future work, the predictive relationships identified here can be developed into a more complete forecast method, and that method can be developed into targeted forecast systems in collaboration with intended end users for the many societal and ecological systems that are shaped by subseasonal patterns of rainfall. The characterization of MJO associations presented in this study provides a foundation for such work.

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Data availability statement. All data used in this study are openly available. CHIRPS v2.0 precipitation data are available from the UC Santa Barbara Climate Hazards Center at https://doi.org/10.15780/G2RP4Q, as cited in Funk et al. (2015). IMERG precipitation data are available from the NASA Goddard Earth Sciences Data and Information Services Center (GES DISC) at https://doi.org/10.5067/GPM/IMERG/3B-HH/06 and documented in Huffman et al. (2015). ERA5 meteorological and atmospheric data are available from the Copernicus Climate Change Service (C3S) Climate Data Store. Precipitation and outgoing longwave radiation (derived from top net thermal radiation) are at https://doi.org/10.24381/cds.adb2d47 and all other variables are at https://doi.org/10.24381/cds.bd0915c6. MERRA-2 meteorological and atmospheric data are available from the Goddard Earth Sciences Data and Information Services Center (GES DISC), with outgoing longwave radiation at https://doi.org/10.5067/Q9OMYPBNVIT and all other variables at https://doi.org/10.5067/VJAPL1ICSIV. OMI data are available from the NOAA Physical Sciences Laboratory at https://psl.noaa.gov/mjo/mjoindex/; as cited in Kiladis et al. (2014). RMM data are available from the Australian Bureau of Meteorology at http://www.bom.gov.au/climate/mjo/ and described in Wheeler and Hendon (2004). All data analysis and visualization were done using NCL version 6.6.2 (UCAR/NCAR/CISL/TDD 2019) in Visual Studio Code (Microsoft Corporation 2022), R version 4.1.2 (R Core Team 2021) in RStudio (RStudio Team 2021), and ArcGIS Pro version 2.9.2 (Esri 2021). Additional R packages used for plotting are ggplot2 (Wickham 2016) and RColorBrewer (Neuwirth 2014).

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